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AIs and Education: Do we really need to worry? Use and perceptions of university students - quasi-global feelings and behaviors

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Abstract. This study presents findings on university students' perceptions and usage habits regarding generative artificial intelligence (GenAI), based on questionnaire responses from students of various academic levels and disciplines across multiple countries (Romania, Iraq, Italy, Argentina, and the Philippines). The results indicate a near-universal adoption of GenAI, with usage largely driven by personal initiative. Most students acquire their knowledge of GenAI applications and form their perceptions independently, relying primarily on online resources rather than expert instruction. While awareness and understanding of GenAI tend to increase with academic progression, they are also influenced by broader cultural contexts; in some cases, gender-related differences are observed. Higher levels of awareness are associated with increased concern about the challenges posed by GenAI, as well as a deeper appreciation of its potential benefits. Students primarily use GenAI to obtain immediate, practical educational advantages. However, there is relatively limited engagement with the broader societal implications—positive or negative—of its use. The primary concern among participants is the impact of GenAI on future employment opportunities. A causal network analysis of the questionnaire data identifies two key outcomes at the end of the causal chain: the level of trust in GenAI-generated results and the degree of personalization in learning processes. Use of GenAI outside academic contexts remains limited, suggesting the emergence of a gap in AI literacy and application in everyday life. To address this issue, it is essential to implement training programs for educators, ensuring that students' acquisition of AI literacy is supported by expert guidance—ideally beginning as early as primary or secondary education.

Keywords: AI usage, Perception on AI, AI in HE, AI pros and cons, causal network, AI and quasi-global patterns.

1 Introduction

A little over two years after the launch of ChatGPT (Chat Generative Pre-trained Transformer), we are witnessing the effects of what can confidently be described as a disruptive innovation. Much like the advent of the World Wide Web over 30 years ago, this technology is rapidly reshaping human behavior across an increasingly wide range of sectors—especially those centered around knowledge as both a subject of study and a foundation for professional activity. This transformative period calls for a deeper investigation into how applications based on Artificial Intelligence are being adopted and used by young people (i.e., school and university students), and how their perceptions of these technologies are evolving. Such inquiry is critical to prevent the consolidation of distorted views or inappropriate use of these tools, to promote adequate levels of awareness, and to identify emerging gaps — technological, educational, or social — that could lead to serious competitive disadvantages in daily life.

Several reports on the use of generative AI among tertiary education students have emerged over the past year. Some belong to the grey literature [1, 2], while others are publicly available and easily accessible. These include the August 2024 DEC (Digital Education Council) survey [3], which gathered responses from nearly 4,000 students across 16 countries, and the early 2025 HEPI (Higher Education Policy Institute) survey [4], which involved just over 1,000 students from the Savanta region. Both reports primarily focus on the extent of AI usage and its purposes among students. The HEPI report additionally examines the relationship between AI use and academic assessment, including students' motivations and concerns. It also explores potential effects related to gender, socio-economic background, and field of study. These findings are discussed in greater detail in Section 4, in relation to our own findings.

The body of scientific literature on this topic is already extensive—so much so that it is difficult to capture comprehensively. Most studies focus specifically on ChatGPT, which is unsurprising given its dominant usage among students, with adoption rates reaching up to 90% in some cases (see Section 3).

Many of these studies, conducted in the latter half of 2023 and early 2024 — when ChatGPT use had become widespread but was still reported by around 50% of students in some regions —investigated the factors influencing technology acceptance. They often employed standard or adapted theoretical frameworks such as the Technology Acceptance Model (TAM) [5, 6], TAME (Technology Acceptance Model Edited to Assess ChatGPT Adoption) [7, 16], integrations of UTAUT (Unified Theory of Acceptance and Use of Technology) [8, 9] and Flow Theory [10, 11], as well as the TOE (Technology–Organisation–Environment) framework [12–14] and TOEK (Technology–Organisation–Environment–Knowledge application) [15]. The size of the datasets used in these studies varied widely, from a few dozen to several thousand participants.

From this literature, key influencing factors emerge: perceived usefulness (i.e., the benefits of using ChatGPT), ease of use, user satisfaction [7, 11, 15, 16], technological reliability (network quality, system responsiveness, accessibility) [15], human-centered interaction [11], positive attitudes towards technology, the ability to affect cognitive/behavioral outcomes, low perceived risk, and low anxiety levels [7].

However, findings on the influence of the educational context or institutional encouragement —referred to as "social influence" or "organisational culture" depending on the model — are mixed. While some studies report a significant influence [7, 15], others find it negligible [11]. Abdaljaleel et al. [7] further identify the influence of variables such as country of residence, age, and academic discipline, while Jo and Bang [15] highlight the importance of knowledge application (i.e., the ability to apply knowledge to problem-solving and decision-making).

Other studies explore attitudes toward ChatGPT across various use cases. Some align with the aforementioned findings [17, 23], while others focus on distinct purposes, such as informing changes to academic integrity policies [18], constructing composite indices for application usage [24], examining effects on critical thinking skills [19], or investigating the impact of academic background [21].

Across these studies, several pragmatic factors are consistently identified as drivers of ChatGPT adoption: easier access to information, time efficiency, flexibility, enhanced academic performance, improved AI literacy [19–21], and support for personalized and self-directed learning [21, 23].

One notable finding by Stöhr et al. [21] is the positive correlation between students' familiarity with and usage of AI chatbots and their attitudes toward them — emphasizing "the importance of the relationship between exposure and practical experience and beliefs about technological innovations in educational contexts" (p. 7). Concerns are also widely reported, such as the risk of misinformation (so-called "hallucinations") [17, 19], which require critical thinking and domain knowledge to detect. Students, however, often accept the content uncritically [19]. Other issues include threats to academic integrity (e.g., plagiarism, cheating) [17, 20, 21], over-reliance on technology [19], diminished critical thinking skills [20], and reduced interpersonal interaction, which may lead to social isolation.

Significant effects based on major and gender have also been noted [21], whereas differences by academic level appear less pronounced. Female students tend to be more skeptical and concerned about AI's impact on learning and assessment. Engineering students show greater optimism, while those from the arts, humanities, medicine, and health care tend to be more cautious—though this contrasts with some findings [22]. Third-cycle (doctoral-level) students are more likely to regularly use a wider range of AI tools. Grájeda et al. [24] also report higher levels of AI usage and competence among students in engineering and economics compared to those in the arts.

Many of the potential advantages and disadvantages of GenAI outlined in the literature are summarized in a collective manifesto signed by over 45 scholars [33].

In light of the above, our investigation aims to provide a more precise understanding of the evolving landscape by pursuing the following objectives:

a) To examine the extent to which the use and penetration of AI-based applications are influenced by:

- a1) digital skill levels;
- a2) educational and social contexts;
- a3) perceived ease of use, usefulness, and efficiency;
- a4) potential effects of gender, academic major, and socio-cultural background.

b) To identify the main perceived benefits and concerns associated with these applications, as well as their perceived impact on students' transversal (transferable) competencies.
c) To explore potential causal relationships among these variables.
d) To assess the level of knowledge and understanding students have of AI-based applications, the extent of their use, and their primary purposes of use as of the first quarter of 2025.

2 The survey

To achieve the objectives outlined in the previous section, we designed a two-part questionnaire comprising 31 items. Section I includes four socio-biographical background questions (gender, age, level of study, and major), along with three questions assessing the perceived level of personal digital competence. Section II consists of 24 items aimed at exploring various dimensions of students' engagement with AI-based applications. Specifically, these items investigate:

- the perceived level of knowledge about AI;
- how students acquire AI-related information;
- their ability to recognize AI-based tools;
- the degree of encouragement provided by their university to use such tools;
- the extent to which AI applications are used independently, including outside of academic contexts;
- the purposes for which these applications are employed;
- the types of applications used and their perceived influence;
- perceived usefulness, efficiency, ease of use, and encountered difficulties;
- the level of trust in AI-generated outcomes, including a comparison with trust in faculty guidance;
- the degree of personalization enabled in learning processes;
- the aspects of AI that are perceived as either concerning or attractive; and
- the transversal skills that students believe are either enhanced or diminished through AI use.

In Section II, 18 questions require either multiple-choice or numerical responses (with three requiring multiple numerical answers), while six items are open-ended or request explanatory comments. Each numerically answered question was used to derive one or more indicators, which are presented in the tables in Appendix A.

No significant fatigue effects due to the length of the questionnaire were observed, as the response rate declined by only a few percentage points between the first and last items.

The questionnaire was translated and administered in Arabic, Spanish, Italian, and English using Google Forms. Distribution was handled by local instructors who shared the survey with their students, except in Iraq, where a more comprehensive dissemination strategy was implemented, involving all universities in the country.

The survey was completed by: 1,512 higher education students from Iraq across various majors; 137 bachelor's and 83 master's students in Computer Science at the University of Craiova; 119 bachelor's students in Computer Science at the

Polytechnic University of Bucharest (UPB); 30 master's students in Italy (mainly in Engineering and Design); 30 bachelor's students in the Philippines (primarily in Computer Science); and 34 bachelor's students in Argentina (mainly in Architecture/Design, Psychology, and Economics).

The potential effect of students' major was examined by segmenting the Iraqi dataset into the following categories: Architecture & Design (38), Computer Science (47), Economics (85), Education (455), Engineering (319), Humanities (58), Law (64), Medicine (388), and STM (58).

Gender effects were analyzed using the full Iraqi dataset and a combined sample of Romanian bachelor's students from the University of Craiova and POLITEHNICA Bucharest.

To investigate the effect of study level, we also included data from a comparable survey administered to Italian high school students, presented in Table 1.

Cultural and educational context effects were explored through a comparative analysis of all collected datasets.

Finally, due to the need for sufficiently large datasets, causal relationships among indicators were studied using only data from Romanian students and Iraqi students enrolled in Education, Engineering, and Medicine programs.

3 Data analysis

For each of the numerical indicators listed in the tables in Appendix A, the descriptive statistical analysis involved calculating the averages and the deviation from the centre of the scale (i.e., 5 for the 0-10 numerical scale;0 for the -5/+5 numerical scale) through a t-test. The black or red stars associated with the mean values indicate the statistical significance of any deviation from the centre of the scale (black in positive, red in negative). For each of the datasets collected, the mean values of the indicators were reported in the tables in Appendix A: mean values for university students in various contexts, except for Iraqi university students in Table 1 (to which were added those for Italian high school students for comparison purposes); mean values for Iraqi university students by majors in Table 2; mean values by gender for Iraqi and Romanian bachelor's students in computer science in Table 3.

Then, in the case of some numerically consistent datasets - Romanian bachelor students in computer science and Iraqi HE students in education, engineering, and medicine - we worked out the network of relations among factors and tried to infer the direction of causality for such associations. More specifically, we used the PC algorithm [25,26] to infer the direction of causality in the graphs reported in section 3.1. Finally, to obtain a bird's-eye view of both intensity and sign of the variables' relations, we employed the paradigm of network analysis (also reported in section 3.1).

3.1 Descriptive Analysis: General Trends and Patterns

Awareness and Competence. A statistically significant trend emerges in the perceived levels of AI information (AIINF) and recognisability of AI applications (AIREC), showing that:

- Master’s students in computer science report higher levels than bachelor's students in the same field.
- Both higher education groups report levels above those of high school students.

This trend may reflect students' self-assessed digital competence levels (see section 3.2). Notably, students consistently rate their general digital competence higher than the specific competencies defined by the European Digital Competence Framework [27].

Cultural context also plays a role: for example, students in countries with lower development indices (e.g., Iraq) or in mixed educational contexts (e.g., Italy, Argentina) tend to report lower AIINF and AIREC, with the exception of more technically oriented students (e.g., engineering and STM majors in Iraq).

Usage vs. Encouragement. Across nearly all datasets—except Iraqi students and a subset of Italian master's students—the actual usage of AI tools exceeds the institutional encouragement to use them. This suggests a growing gap between students' adoption and faculty endorsement and support. The web is the dominant source of AI knowledge (~90%), followed by peer interactions. University faculty and dedicated coursework rarely serve as primary sources (only in highly specialized technical contexts), highlighting a gap in formal AI literacy initiatives.

Usage Contexts. Students overwhelmingly use AI tools in educational settings more than in everyday life or hobbies. The most frequently used application is ChatGPT, adopted by 85–90% of university students and 70% of high school students. Tools like Copilot, Gemini, and Claude have far lower usage rates (10–20%).

The most common use cases are: Content search (70–85%); Problem solving (60–65%); Assignment support (53–60%).

More advanced or creative uses — e.g., critical analysis (~30%), image generation, or media post-production — remain limited. Very few students (<15%) report using AI for professional-level tasks (e.g. to generate and post-produce videos and/or sounds).

Perceived Outcomes and Confidence. Students perceive a moderate to high level of personalisation (actually self-personalization) in learning processes, typically above the midpoint of the scale. The highest personalisation score (6.85/10) was reported by undergraduate computer science students at the University of Craiova.

Confidence in generative AI outputs is also consistently above average (5.5–6.7), with a notable exception: master's students at Craiova (7.49), who may engage with these tools in more specialised contexts such as programming.

Despite the widespread use of generative AI, students generally trust their faculty more than the tools, especially in more developed or specialised academic settings.

This trust differential narrows in less developed (e.g., Iraq) or less specialised contexts (e.g., high schools).

The perceived influence of AI on personal opinion remains moderate (just above scale midpoint), with higher scores observed in more advanced or specialised environments (around 6.5/10).

Technology Acceptance and Attitudes. Indicators commonly associated with the Technology Acceptance Model (TAM) — particularly usefulness and ease of use — receive strong endorsement, with scores significantly above the midpoint (from one and a half to almost three and a half points higher). Perceived effectiveness also scores above average, though to a lesser extent. Quite possibly, however, those considered by TAM model are not the only relevant factors in the adoption of AIs-based technologies (see for example the case of the adoption of educational technologies following the spread of the Covid [28] and the other studies cited in the introduction) but certainly represent an important contribution in contexts where immediate, effective and practical answers are sought, as shown by the reports and the papers cited in the introduction and in [29].
Interest in AI grows with academic level. Students particularly value AI's contributions to: Resource optimisation; Human–AI integration; Error reduction and problem-solving

Concerns and Awareness Gaps. Perceptions of risk vary significantly across indicators. The most prominent concerns include: False or misleading information; Stereotypical or biased outputs**;** Privacy risks.

Surprisingly, students are less concerned about AI addiction and even less about broader societal impacts (e.g., threats to democracy, ethical concerns, environmental impact, gender/racial bias). As previously noted [29], this reflects a lack of guided critical engagement and structured AI literacy. Interestingly, higher AIINF scores correlate with increased concern and interest, suggesting that better-informed students are more capable of critically reflecting on both AI's benefits and its risks.

The notably low concern over gender/racial bias could reflect deeper cultural differences. In regions like the Anglo-Saxon world — more historically conscious of systemic inequality — such issues receive greater attention, likely influencing perceptions.

3.2 Descriptive Analysis: The influence of the majors: The case of the Iraqi HE students

As previously discussed, the level of study clearly influences students' perceptions and attitudes toward AI. The case of Iraqi higher education students, owing to the large and varied dataset, enables a deeper exploration of the role played by students' academic majors. Table 2 in Appendix A presents comparative data from nine distinct fields of study, revealing a notable differentiation in the average values of the indicators based on the discipline.

Students from majors such as Engineering, STM, and Computer Science exhibit the highest average values across most indicators—especially regarding their perceived knowledge of AI (AIINF) and engagement with AI-based tools. These values approach or slightly surpass those observed among Italian high school students, suggesting a relatively robust exposure to or interest in technological domains. Similarly, students in Economics and Architecture & Design show higher-than-average engagement, particularly in the practical use of AI tools. In contrast, students from the Education, Law, and Humanities majors report significantly lower average values across nearly all dimensions, indicating a more limited integration or familiarity with AI technologies in their academic or personal routines.

Interestingly, in contrast with trends observed in other national contexts, Iraqi students perceive faculty encouragement to adopt AI-based applications and tools as stronger than their own actual engagement. This may reflect a mismatch between institutional aspirations and the practical limitations or hesitations faced by students. Nevertheless, other patterns mirror those described in the previous section for the case of other datasets.

One particularly distinctive feature of the Iraqi dataset is the exceptionally low level of concern regarding the ethical and societal risks associated with AI. In addition to the very low perceived risk of gender or race bias, students reported similarly minimal concern about issues such as the lack of conscience or ethical grounding in AI systems, or potential threats to democratic processes. These findings suggest that, in this context, such dimensions are not perceived as particularly relevant or urgent. Conversely, there is a relatively high level of concern regarding the potential loss of human skills due to the adoption of AI.

Among the majors, Economics students stand out for their strong attraction to AI-based tools—on par with Computer Science students and even more so than Engineering students. This may reflect an anticipation of AI's growing role in business analytics, finance, and related sectors, where these students likely envision their future careers.

3.3 Descriptive Analysis: Gender and cultural background

The influence of gender on students' engagement with and perceptions of AI was examined using the two most substantial datasets collected: the full cohort of Iraqi students and the more specialized group of Romanian bachelor's students in Computer Science. The results of this analysis, summarised in Table 3 of Appendix A, reveal both context-specific patterns and broader cultural dynamics.

In the Iraqi sample, gender-based disparities are clearly visible. Male students report higher average values across most of the measured indicators—particularly in self-perceived digital competence, familiarity with AI, and actual usage of AI tools. These differences are statistically significant in many cases and point to a gender gap in digital and AI-related literacy. However, when it comes to the perceived risks associated with AI technologies, these gender differences largely vanish. Both male and female students report similarly low levels of concern across most dimensions, although males exhibit a slightly higher interest in AI's potential applications.

The Romanian dataset, in contrast, presents a more balanced and nuanced picture. While differences do exist, they do not follow a clear gendered pattern. Female students, for instance, rate themselves as more competent in digital content creation, information management, and interaction with digital technologies. Meanwhile, male students report higher perceived knowledge about AI (AIINF) and better recognition of AI applications (AIREC). Yet, when it comes to actual use, female students demonstrate slightly greater integration of AI tools into their learning processes—corresponding with a higher reported level of personalization in their learning experience. Males tend to use AI more for other tasks.

Further, Romanian female students display slightly more positive perceptions concerning the trustworthiness, usefulness, and usability of AI-based applications. Notably, they also report higher levels of both concern and interest in the broader implications of AI, with statistically significant differences in several cases. Whether these responses reflect deeper engagement, a higher degree of empathy, or simply different usage patterns remains open to interpretation.

What becomes evident through this comparative lens is that gender effects, unlike those tied to study level or academic major, are not uniformly distributed across contexts. Rather, they appear strongly influenced by cultural and educational environments. In societies where digital divides or traditional gender roles are more pronounced, like Iraq, these effects are magnified..

3.4 Causal networks

One of the key objectives of this study was to go beyond a descriptive understanding of students' opinions on AI and their usage of AI-based applications. While average indicator values provide useful insights, they offer a limited view of the underlying dynamics. To this end, we sought to uncover potential correlations and causal relationships among the indicators used in our survey. This analysis required robust datasets. We thus focused on responses from Romanian bachelor's and master's students in Computer Science (359 records) and, for comparative purposes, on the Iraqi datasets in Education (455), Engineering (319), and Medicine (388).

Figures 1 and 3 present the causal networks for Romanian and Iraqi students, respectively. To contextualise the strength and relevance of these relationships, Figure 2 displays the correlation network for Romanian students, with selected links labelled according to intensity (e.g., VS = very strong, S = strong). Figure 4 illustrates the correlation network for the Iraqi cohorts. This combination allows us to interpret both the direction of influence (from causal analysis) and the strength and perceived importance (from correlations and average values).

Two characteristics of the correlation networks stand out immediately:

• Positive correlations dominate, with few and generally weak negative relationships.

• The indicators cluster into four loosely connected blocks: digital competences, concerns, interests, and general indicators. This structural segmentation may stem partly from the survey design—specifically, matrix-based questions—but likely also reflects a fragmented mental model among students, with limited integration between themes. This fragmentation may, in turn, be rooted in a low level of overall awareness about AI and its implications.

Internal Structure of Digital Competences. Going into the detailed analysis of the causal networks we can see that in the case of the Romanian dataset (Fig. 1), the only connection between digital competences and other survey indicators is between overall digital competence (IDC) and knowledge of AI (AIINF). Notably, IDC alone—not its individual components—shows this link, suggesting that students perceive IDC as a broader or more abstract concept than the composite digital skills defined in frameworks such as DigComp 2.2 [27]. In fact, IDC consistently scores higher than its component skills in nearly all datasets.

Within the Romanian network, IDC is causally connected to only one component skill: IDC5 (problem-solving in digital environments). More generally, however, the structure of relationships among the component digital competences varies by context. Among Romanian students, IDC2 (interaction through digital tools) appears upstream, strongly influencing IDC5 and IDC3 (content creation), and—along with IDC4 (data protection)—contributes to IDC1 (information management), which serves as the terminal skill. Among Iraqi students, the terminal skills differ: IDC3 in Education, IDC4 in Engineering, and IDC1 again in Medicine.

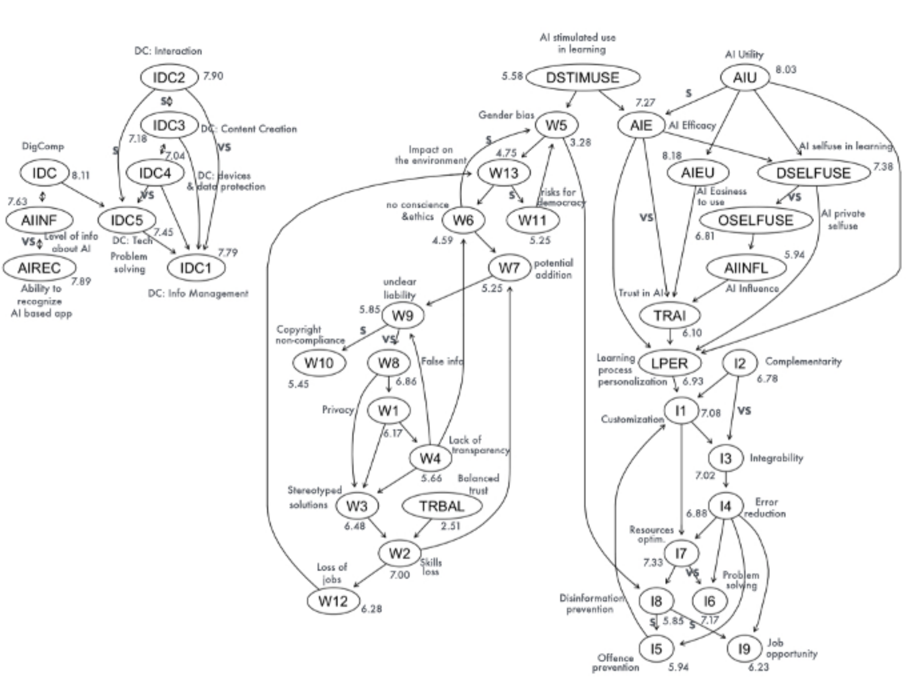

Fig.1. Causal network between the indicators used in the survey for the case of Romanian bachelor's & master's students in computer science. The figure also shows the average values calculated for each indicator and the link intensity between indicators (strong = S; very strong = VS) as deduced from the correlation network shown in Fig. 2.

AI Knowledge, Use, and Perception. AIINF is closely linked to AIREC, though the direction of causality remains ambiguous. In Fig. 1, AIINF and AIREC are connected only to IDC, while in the other networks, AIINF is weakly connected to the individual use of AI-based applications and tools (DSELFUSE or OSELFUSE), while AIREC is weakly connected to the perceived ease of use of such applications/tools (AIEU).

Use in learning processes (DSELFUSE) influences use in other domains (OSELFUSE). However, the role of teacher stimulus (DSTIMUSE) remains unclear. In all cases except the Iraqi one, students report receiving less stimulation from faculty than the extent to which they independently use AI, suggesting a gap in institutional encouragement.

Two important terminals in the causal chains are: *Trust in AI outcomes (TRAI*) and *Perceived personalisation of learning (LPER)*.

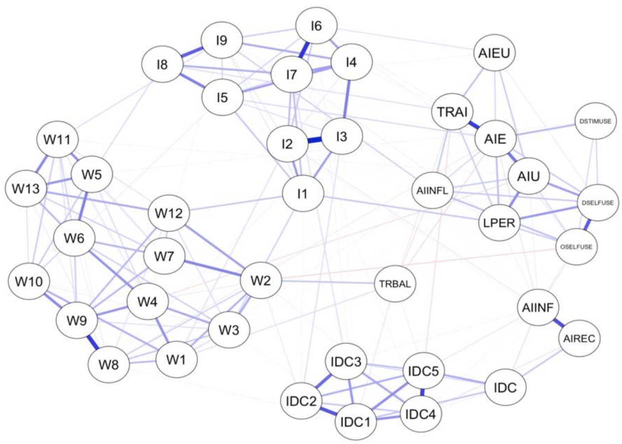

Fig.2. Causal network between the indicators used in the survey for the case of Romanian bachelor's & master's students in computer science. In blue - the positive correlations, in red - the negative ones

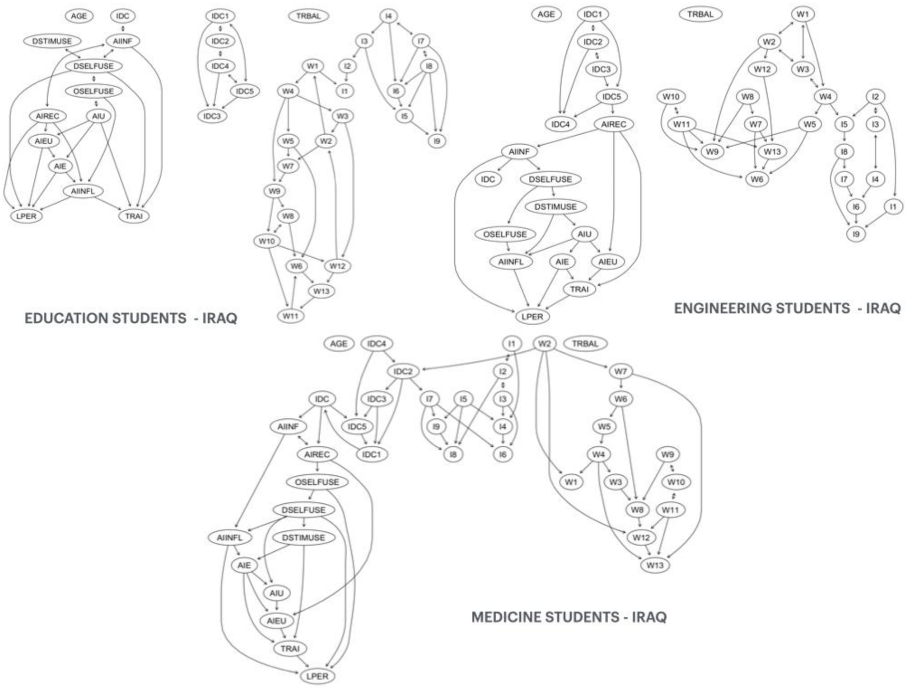

Fig. 3. Causal network between the indicators used in the survey for the case of Iraqi students in Education, Engineering, and Medicine.

In most of the causal networks shown in Figures 1 and 3, TRAI feeds into LPER, and this latter can be shaped by several factors, including: Independent AI use (DSELFUSE), Perceived influence of AI on opinions (AIINFL), Usefulness (AIU), effectiveness (AIE), and ease of use (AIEU).

AIU, AIE, and AIEU form a tightly connected sub-network, reinforcing TRAI across all datasets. These findings suggest that, while Technology Acceptance Model (TAM) variables remain important, other dimensions—such as influence on learning and opinion formation—also shape students' trust and engagement with AI.

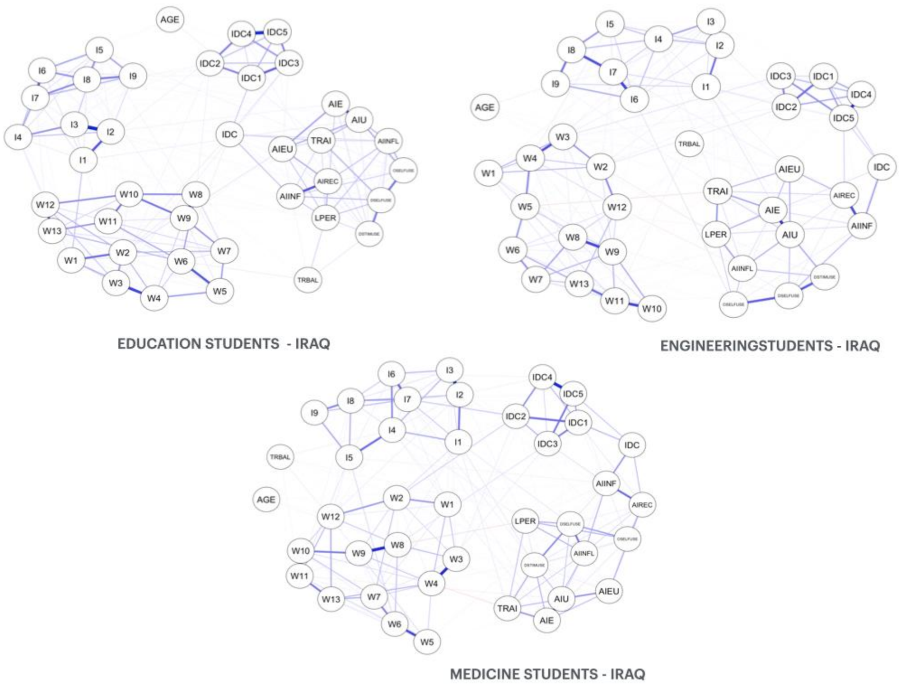

Fig. 4. Causal network between the indicators used in the survey for the case of Iraqi students in Education, Engineering, and Medicine. In blue - the positive correlations, in red - the negative ones.

Interests and Concerns: Context-Specific Patterns. The causal networks for interest and concern indicators are more variable across contexts. While terminal points differ, one element appears repeatedly as the endpoint in the interest network: job opportunities that AI might generate (I9). The exception is Iraqi medical students, for whom terminal points include problem solving (I6) and misinformation prevention (I8).

In the following, due to the differences in patterns we examine, by way of exemplification only the sub-network of the elements of interest for the case of the Romanian students (Fig. 1): LPER leads to interest in personalisation (I1); the perceived complementarity between humans and AIs (I2) drives interest in their integrability (I3), which cascades into concern for error reduction (I4), resource optimisation (I7), and problem solving (I6). Optimisation, in turn, supports misinformation prevention (I8), ultimately feeding expectations of job creation (I9).

As for concerns, coherently, the most prominent terminal indicator is the fear of job loss (W12). This is linked causally to perceived risks of skill degradation (W2) and the perpetuation of stereotypes (W3) — the latter possibly interpreted as a reduction in creative latitude, a quintessentially human trait [30].

These interpretations align with direct survey responses. Romanian students ranked creativity (53% in Craiova, 67% in Bucharest) and critical thinking (52% Craiova, 60% Bucharest) as the most threatened life skills. In Iraq, the greatest concerns were for the loss of problem-solving ability (54%) and problem posing (49%), with creativity (36%) in third place.

Perceived potential for skill enhancement through AI also differed culturally. Romanian students identified problem solving (>56% Craiova and > 61% Bucharest), data planning and analysis (>45% Craiova and > 54% Bucharest), flexibility (>48% Craiova and > 49% Bucharest), problem setting (>46% Craiova and > 39% Bucharest), and evaluation skills (>29% Craiova and > 41% Bucharest) as likely beneficiaries. Iraqi students, in contrast, reported lower confidence in AI's capacity to enhance human capabilities. Their top responses included creativity (29%, surprisingly in first place), self-confidence (25%), teamwork (22%), and critical thinking (22%), with generally lower overall percentages. This may indicate both a cultural scepticism and a less developed awareness of AI's potential.

4 Discussion, Final Recommendations, and Future Work

This study, leveraging multiple datasets, provides a comprehensive view of the state of AI-based application use among university students as of early 2025. It not only captures a snapshot of current practices but also reveals recurring patterns across diverse cultural and educational settings. The breadth of the data enabled an investigation into potential causal relationships among key indicators.

A consistent picture emerges that confirms and builds on previous findings. The penetration of generative AI tools among students is nearly total in developed countries—approaching 100%—up from 84% in 2024 [3] and 92% in early 2025 [4]. ChatGPT dominates usage, cited by 85–90% of students, fulfilling a role comparable to Google in earlier decades. Other AI chatbots remain peripheral, used by fewer than 20% of students.

However, the current use of AI remains concentrated on text-based applications. The adoption of generative AI for image, video, or music tasks is growing more slowly. This discrepancy may reflect educational priorities: while literacy in reading and writing is foundational and taught early, skills in multimedia content creation are less developed, even as passive consumption grows. Furthermore, AI tools are predominantly used within academic contexts and have yet to see widespread integration into daily life — a missed opportunity for fostering digital citizenship and broader societal engagement.

Causal analysis reveals that students' use of AI in higher education is primarily driven by perceived usefulness, reinforced by the ease of use. These factors build trust in AI outputs, which leads to a favorable perception of personalized learning. Students, aligning with [4]: see AI as a means of saving time, receiving round-the-clock assistance, and improving their academic performance. Ultimately, it is the perception of clear, immediate benefits that shapes technology acceptance.

Another key insight is the pivotal role of awareness and understanding. Trust in AI is strongly influenced by students' ability to recognize how AI functions and where it is embedded. These abilities increase with the level of education, reinforcing the need for comprehensive AI literacy.

Alarmingly, faculty and institutions are not consistently providing the necessary support. Their role is uncertain and cannot be taken for granted. Our findings show that most students develop their AI literacy informally—through web browsing and peer-to-peer interactions—rather than through structured institutional efforts. This has revealed a significant gap between faculty/institutions and students. Without expert guidance, students rely more on perceived short-term benefits than on a comprehensive understanding of AI's capabilities, limitations, and risks. At the same time, institutional efforts seem focused more on regulating AI usage and updating assessment procedures [3, 4], often in a reactive attempt to prevent cheating or plagiarism. Instead, we propose fostering a collaborative space where educators and institutions can guide students toward the ethical and informed use of AI. This requires first investing in the training of educators and recognizing that student literacy cannot be left solely to higher education. Our findings among high school students point to the need for earlier interventions and for including pre-service teacher training—potentially using frameworks such as the DEC AI Literacy Framework [31].

Additional support for this argument is found in the high priority students assign to the issue of job creation and destruction due to AI—while their concern about broader social and environmental risks remains low. This contrast further emphasizes the need for comprehensive AI literacy that includes ethical, societal, and environmental awareness.

The study also confirms the presence of gender and disciplinary effects, as reported in [4, 21, 24], which vary based on socio-cultural context. This is a matter of concern due to the risk of widening digital divides. As [21] suggests, these disparities underline the need for tailored approaches to AI education that consider the diverse backgrounds and needs of students.

A final important reflection concerns the cognitive shifts—or “brainframe changes” [32] — brought about by the integration of AI, similar to past revolutions in communication and information use. Such changes inevitably influence behavior and reshape the human skills that distinguish us from machines [30]. Our data show that students are only moderately concerned about over-reliance or addiction to AI tools, and they generally believe they can manage the influence of AI-generated content on their opinions (with the AIINFL indicator correlating positively with AI awareness). However, there is significant concern about the potential loss of key competencies. For instance, Romanian, Argentinean, and Filipino students highlighted creativity and critical thinking, while Italian students noted a decline in autonomy and relational skills. In Iraq and the Philippines, concerns focused on problem-solving and problem-setting abilities.

Although the specific competencies identified as "at risk" vary across regions—likely due to socio-cultural and educational factors—it is clear that AI literacy efforts must go beyond technical skills. They must include awareness of the value of life skills and adopt teaching methods that preserve and strengthen competencies vulnerable to erosion in an AI-driven environment.

Final Recommendations.

• Promote Comprehensive AI Literacy - Institutions should integrate AI education across all levels—starting from secondary school—emphasizing not only functionality but also ethics, limitations, and long-term impacts. Frameworks like the DEC AI Literacy Framework [31] can provide a useful starting point.

• Bridge the Institutional Gap - Faculty and administrative bodies must move from a policing approach to a partnership model with students. Structured, co-designed educational interventions can help students use AI tools consciously and ethically.

• Tailor Support by Demographic and Context - Gender, field of study, and cultural background influence how students interact with AI. AI literacy programs must be flexible and inclusive, ensuring no group is left behind.

• Protect and Reinforce Life Skills - AI education should actively preserve key human competencies—such as creativity, autonomy, and interpersonal skills—that may be at risk. Programs should include reflective, project-based, and collaborative learning strategies.

• Train the Trainers - Faculty development is essential. Teachers and academic staff must be equipped not only to use AI tools themselves but also to guide students in their use. Pre-service teacher education should also embed AI literacy.

• Encourage Everyday AI Usage Beyond Academics - Students should be encouraged to apply AI tools beyond coursework, such as in civic engagement, environmental awareness, and personal development, fostering holistic digital citizenship.

Future Work. Although the present study provides substantial insight, certain limitations remain— notably, the unequal size of datasets and the reliance on self-reported data. These factors may affect the generalizability of findings and warrant further investigation.

Planned future steps include:

• Expanding the Dataset - Collecting more data from underrepresented regions and socio-cultural contexts to ensure broader applicability of the findings.

• Qualitative Analysis - Analyzing students' open-ended responses to better understand the nuances of their experiences, motivations, and concerns related to AI.

• Stakeholder Needs Assessment - Conducting focused studies to understand what students, faculty, and institutions need in order to foster meaningful AI literacy.

• Designing Intervention Models - Based on future findings, develop and test targeted educational interventions to support responsible, inclusive, and impactful AI use in higher education and beyond.

Ultimately, our aim is to contribute to the formation of smart, responsible citizens equipped to harness AI not just in learning but also in building a socially equitable and environmentally sustainable future..

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Appendix A

Table 1. Mean values of the survey indicators (defined in the first column on the left) reported for the sets of university students who participated in the survey: bachelor students in Computer Science UPB (Bach B), bachelor students in Computer Science Craiova university (Bach C), master students in Computer Science Craiova university (Master C), master students in Computer Science and Interaction Design University of L'Aquila and Siena (MasterIT), bachelor students in Computer Science (Bach Ph), bachelor students in Architecture (Bach Arg). The mean values of the survey indicators extracted from a similar survey carried on with high school students from several Rome's schools (HS Italy) have been also reported for comparison.
The stars indicate the statistical significance of the t-test with respect to the central value of the scale, 5, for all the indicators except TRBAL (*) for which the central value of the scale is 0.

Indicator	**Mean HS Italy**	**Mean Bach B**	**Mean Bach C**	**Mean Master C**	**Mean MasterIT**	**Mean Bach Ph**	**Mean Bach Arg**
Individual Digital Skills (IDC)	7.05*** [6.88-7.22]	8.05*** [5.66-6.17]	7.71*** [7.44-7.98]	8.79*** [8.53-8.06]	7.57*** [6.97-8.16]	6.31** [5.51-7.11]	7.03*** [6.50-7.56]
Digital Skills: information management (IDC1)	5.71*** [5.36-6.05]	7.95*** [7.59-8.31]	7.52*** [7.11-7.94]	7.88*** [7.32-8.44]	7.90*** [6.02-7.78]	5.83 [4.91-6.75]	6.60** [5.70-7.51]
Digital Skills: interaction (IDC2)	5.84*** [5.50-6.19]	8.16*** [7.82-8.50]	7.66*** [7.24-8.08]	7.90*** [7.36-8.45]	7.00*** [6.17-7.83]	6.13* [5.11-7.15]	6.74*** [5.80-7.67]
Digital Skills: digital content creation (IDC3)	5.30 [4.94-5.66]	7.27*** [6.86-7.67]	6.93*** [6.51-7.34]	7.41*** [6.86-7.96]	6.80*** [5.86 -7.74]	5.90 [4.91-6.89]	5.70 [4.66-6.74]
Digital Skills: devices and personal data protection (IDC4)	5.17 [4.82-5.51]	7.34*** [6.94-7.44]	6.54*** [6.09 6.98]	7.36*** [6.84-7.94]	5.90 [4.93 6.87]	6.23* [5.20-7.27]	5.85 [4.75-6.95]
Digital Skills: technical problem solving (IDC5)	4.74 [4.39-5.09]	7.60*** [7.24-7.95]	6.96*** [6.54-7.38]	7.90*** [7.37-8.44]	5.77 [4.69-6.84]	5.67 [4.71-6.62]	5.30 [4.27-6.34]

Level of information owned about AI (AIINF)	6.22*** [5.98-6.45]	7.41*** [7.13-7.69]	7.60*** [7.33-7.86]	7.89*** [7.51-8.27]	6.20*** [5.57-6.83]	7.40*** [6.70-8.10]	6.21*** [5.71-6.71]
Ability to recognize AI based applications (AIREC)	6.25*** [5.98-6.45]	7.83*** [7.56-8.10]	7.73*** [7.45-8.00]	8.16*** [7.84-8.48]	6.60*** [5.95-7.25]	8.37*** [7.83-8.91]	5.76* [5.02-6.51]
Stimulation to use AI based applications in learning processes (DSTIMUSE)	5.79*** [5.47-6.12]	4.68 [4,20-5,16]	5.22 [4.76-5.68]	6.87*** [6.31-7.43]	7.70*** [6.91-8.49]	6.97*** [5.89-8.04]	4.12* [3.30-4.93]
Autonomous use of AI based applications in learning processes (DSELFUSE)	5.58*** [5.26-5.90]	6.60*** [6.17-7.02]	7.49*** [7.18-7.81]	8.00*** [7.60-8.40]	6.47 [5.51-7.43]	7.23*** [6.31-8.16]	5.47 [4.65-6.29]
Autonomous use of AI based applications in other contexts (OSELFUSE)	4.94 [4.62-5.26]	5.84** [5.33-6.36]	6.95*** [6.50-7.40]	7.60*** [7.12-8.09]	5.83 [4.73-6.94]	6.30* [5.21-7.39]	4.82 [3.89-5.75]
Level of influence generated by AI based applications (AIINFL)	4.32*** [4.02-4.62]	5.30 [4.84-5,76]	5.82*** [5.41-6.24]	6.88*** [6.39-7.37]	5.17 [4.39-5.94]	6.57* [5.59-7.55]	4.35 [3.37-5.33]
Usefulness of AI based applications (AIU)	7.09*** [6.85-7.33]	7.57*** [7.22-7.93]	8.11*** [7.82-8.40]	8.34*** [7.94-8.73]	7.83*** [7.13-8.53]	8.20*** [7.35-9.05]	7.32*** [6.62-8.03]
Effectiveness of AI based applications (AIE)	6.83*** [6.59-7.08]	6.60*** [6.21-6.98]	7.29*** [7.00-7.58]	7.90*** [7.50-8.31]	6.59*** [5.94-7.23]	7.73*** [6.98-8.49]	7.14*** [6.49-7.80]
Easiness to use AI based applications (AIEU)	7.89*** [7.65-8.12]	8.10*** [7.75-8.46]	8.06*** [7.76-8.37]	8.33*** [7.94-8.72]	7.73*** [7.12-8.35]	8.17*** [7.56-8.77]	7.59*** [6.81-8.37]
Trust in the outcomes	6.20***	5.56**	6.11***	7.49***	5.57	6.20**	6.44***

of AI based applications (TRAI)	[5.96-6.44]	[5.21-5.91]	[5.76-6.46]	[7.11-7.88]	[4.81-6.32]	[5.52-6.88]	[5.79-7.09]
Balanced Trust Teachers/AI (TRBAL) (*)	1.74*** [1.46-2.03]	3.15*** [2.82-3.46]	2.25*** [1.85-2.65]	2.02*** [1.55-2.49]	3.33*** [2.91-3.75]	2.63*** [1.75-3.52]	2.30*** [1.55-3.06]
Personalization of the learning process (LPER)	5.49*** [5.21-5.77]	6.40*** [5.93-6.81]	6.85*** [6.49-7.20]	7.49*** [7.11-7.88]	5.93 [5.04-6.83]	6.60*** [5.80-7.40]	4.94 [4.05-5.83]
Level of concern about privacy (W1)	5.51** [5.20-5.86]	6.13*** [5.80-6.68]	5.87*** [5.36-6.37]	6.39*** [5.72-7.05]	6.48** [5.42-7.54]	6.72** [5.59-7.86]	6.44* [5.28-7.60]
Level of concern about loss of skills (W2)	6.32*** [5.96-6.69]	7.34*** [6.89-7.80]	6.93*** [6.47-7.38]	6.34*** [5.72-6.96]	7.07*** [5.97-8.16]	7.03*** [5.94-8.13]	6.15* [5.04-7.27]
Level of concern about stereotyped solutions (W3)	5.19 [4.86-5.52]	6.32*** [5.83-6.81]	6.38*** [5.91-6.85]	6.54*** [5.96-7.12]	7.50*** [6.42-8.38]	6.07 [4.89-7.26]	6.03 [4.95-7.26]
Level of concern about lack of transparency (W4)	4.99 [4.65-5.34]	5.30 [4.80-5.80]	5.60** [5.16-6.04]	6.01** [5.37-6.65]	6.23* [5.21-7.26]	5.82 [4.71-6.93]	5.94 [4.86-7.01]
Level of concern about gender/race bias (W5)	4.13*** [3.76-4.49]	2.76*** [2.20-3.31]	3.03*** [2.54-3.52]	4.34 [3.60-5.07]	4.41 [3.23-5.59]	4.69 [3.39-5.99]	4.22 [2.92-5.51]
Level of concern about absence of conscience&ethics (W6)	5.25 [4.88-5.62]	4.58 [3.97-5.19]	4.40 [3.86-4.95]	4.69 [3.96-5.41]	5.53 [4.38-6.68]	5.71 [4.61-6.82]	4.91 [3.60-6.21]
Level of concern about possible addiction (W7)	5.51** [5.14-5.88]	5.39 [4.77-6.02]	4.90 [4.36-5.45]	5.36 [4.63-6.09]	5.57 [4.42-6.72]	5.96 [4.62-7.31]	4.97 [3.71-6.23]
Level of concern about generation of false information	6.06*** [5.69-6.44]	6.97*** [6.44-7.51]	6.87*** [6.35-7.38]	6.29*** [5.61-6.97]	6.83*** [5.82-7.85	6.55* [5.18-7.93]	7.00*** [5.92-8.08]

(W8)							
Level of concern about unclear liability (W9)	5.11 [4.74-5.47]	5.77** [5.25-6.29]	5.72** [5.19-6.25]	5.88** [5.25-6.51]	5.33 [4.19-6.48]	5.97 [4.71-7.22]	5.84 [4.80-6.89]
Level of concern about non-compliance with copyright (W10)	5.00 [4.61-5.40]	5.24 [4.63-5.84]	5.38 [4.84-5.92]	5.75* [5.04-6.45]	6.50** [5.42-7.58]	6.28* [5.07-7.48]	5.50 [4.30-6.70]
Level of concern about risk for democracy (W11)	4.28*** [3.91-4.65]	4.44 [3.83-5.06]	4.12** [3.57-4.68]	4.76 [4.01 5.51]	4.73 [3.57-5.89]	5.55 [4.34-6.77]	4.75 [3.53-5.97]
Level of concern about greater difficulty to find a job (W12)	5.86*** [5.47-6.25]	6.24*** [5.67-6.82]	6.49*** [5.96-7.01]	5.71* [5.01 6.41]	5.60 [4.38-6.82]	6.14 [4.82-7.46]	5.56 [4.26-6.87]
Level of concern about negative impact on environment (W13)	4.73 [4.34-5.12]	4.68 [4.04-5.32]	4.51 [3.95-5.07]	4.87 [4.10 5.63]	4.80 [3.52-6.09]	5.62 [4.36-6.88]	4.25 [2.95-5.55]
Level of interest determined by customization (I1)	5.16 [4.83-5.50]	7.06*** [6.62-7.50]	6.62*** [6.16-7.09]	7.60*** [7.08 8.13]	6.60** [5.61-7.59]	6.20* [5.07-7.33]	5.75 [4.8-6.68]
Level of interest determined by complementarity with human capability (I2)	5.49** [5.16-5.82]	6.41*** [5.93-6.89]	6.71*** [6.25-7.17]	7.07*** [6.48 7.66]	5.70 [4.59-6.81]	6.20* [5.05-7.35]	6.00* [5.10-6.90]
Level of interest determined by integrability with human capability (I3)	5.81*** [5.47-6.15]	6.72*** [6.27-7.17]	6.95*** [6.51-7.39]	7.30*** [6.74-7.86]	7.40*** [6.59-8.21]	6.43* [5.36-7.51]	6.31* [5.30-7.32]
Level of interest determined by	5.85*** [5.50-6.20]	6.45*** [5.95-6.95]	6.79*** [6.33-7.24]	7.42*** [6.85-7.99]	6.20** [5.35-7.05]	6.10 [4.98-7.22]	6.53* [5.39-7.67]

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reduction of human error (I4)							
Level of interest determined by preventing offences (I5)	5.00 [4.64-5.35]	5.48 [4.96-6.00]	5.76** [5.29-6.23]	6.99*** [6.38-7.60]	4.72 [3.62-6.83]	6.10 [4.98-7.22]	6.41* [5.30-7.51]
Level of interest determined by optimized finding of links among elements & problem solutions (I6)	6.12*** [5.77-6.48]	6.96*** [6.49-7.43]	7.07*** [6.62-7.51]	7.41*** [6.82-8.00]	7.33*** [6.42-8.24]	6.23* [5.17-7.30]	6.62** [5.60-7.65]
Level of interest determined by optimization of resources usage (I7)	6.19*** [5.84-6.54]	7.25*** [6.80-7.70]	7.10*** [6.62-7.57]	7.71*** [7.20-8.22]	7.43*** [6.55-8.31]	6.23** [5.42-7.51]	7.59*** [6.68-8.50]
Level of interest determined by prevention of disinformation (I8)	5.66*** [5.32-6.01]	5.46 [4.91-6.01]	5.53 [5.29-6.23]	6.82*** [6.20-7.43]	5.03 [3.96-6.11]	5.77 [4.67-6.87]	6.31*** [5.30-7.32]
Level of interest determined by more job opportunities (I9)	5.0 [4.94-5.66]	5.97** [5.39-6.55]	6.07*** [5.57-6.58]	6.89*** [6.27-7.51]	6.17* [5.09-7.24]	5.60 [4.45 6.75]	6.97*** 6.01-7.93]

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Table 2. Mean values of the survey indicators (defined in the first column on the left) reported for the sets of Iraqi university students who participated in the survey grouped by their majors: Education (Mean Edu); Engineering (Mean Eng); Medicine (Mean Med); Economy (Mean Econ); Law (Mean Law); Humanities (Mean Hum); Architecture & Design (Mean Arc&Des); Hard Science, Technology and Math (Mean STM); Computer Science (Mean CS). The stars indicate the statistical significance of the t-test with respect to the central value of the scale, 5, for all the indicators except TRBAL (*) for which the central value of the scale is 0.

Indicator	Mean Edu	Mean Eng	Mean Med	Mean Econ	Mean Law	Mean Hum	Mean Arc&Des	Mean STM	Mean CS
Individual Digital Skills (IDC)	6.88*** [6.69-7.07]	6.87*** [6.65-7.08]	6.33*** [6.12-6.54]	6.93*** [6.51-7.35]	6.83*** [6.37-7.28]	6.37*** [5.77-6.98]	6.13** [5.38-6.88]	6.81*** [6.34-7.28]	7.20*** [6.53-7.68]
Digital Skills: information management (IDC1)	4.06*** [3.77-4.34]	5.25 [4.92-5.59]	4.83 [4.54-5.11]	5.20 [4.54-5.86]	4.25 [3.44-5.06]	3.74* [3.00-4.49]	4.34 [3.39-5.29]	5.16 [4.38-5.95]	4.77 [3.76-5.77]
Digital Skills: interaction (IDC2)	4.86 [4.54-5.19]	6.04*** [5.69-6.40]	5.79*** [5.49-6.08]	5.99* [5.49-6.08]	5.16 [4.32-6.00]	4.93 [4.01-5.85]	5.11 [4.08-6.13]	5.77 [4.98-6.57]	5.44 [4.48-6.41]
Digital Skills: digital content creation (IDC3)	3.98*** [3.68-4.28]	4.66* [4.31-5.01]	4.31*** [4.02-4.60]	4.75 [4.00-5.50]	3.77** [2.95-4.59]	4.07 [3.15-5.00]	3.63** [2.75-4.52]	5.00 [4.20-5.80]	4.55 [3.47-5.62]
Digital Skills: devices and personal data protection (IDC4)	4.59** [4.17-4.81]	5.38* [5.02-5.74]	4.86 [4.55-5.16]	5.34 [4.54-6.13]	3.87** [3.12-4.62]	4.45 [3.50-5.41]	4.05 [3.03-5.07]	5.36 [4.51-6.22]	4.61 [3.52-5.71]
Digital Skills: technical problem solving (IDC5)	4.08*** [3.77-4.39]	4.95 [4.58-5.32]	4.37*** [4.06-4.67]	4.81 [4.04-5.58]	3.64*** [2.91-4.37]	4.06* [3.17-4.94]	3.49** [2.52-4.46]	4.98 [4.12-5.84]	5.07 [3.99-6.17]
Level of information owned	5.84*** [5.60-	6.20*** [5.96-	5.62*** [5.38-	5.98*** [5.46-5.49]	5.43 [4.82-	5.84** [5.22-	5.82 [4.96-6.67]	6.19*** [5.53-	5.89* [5.17-

about AI (AIINF)	6.08]	6.45]	5.86]		6.04]	6.46]		6.85]	6.61]
Ability to recognize AI based applications (AIREC)	5.71*** [5.47-5.95]	6.24*** [5.97-6.50]	5.58*** [5.53-6.04]	6.19*** [5.66-6.72]	5.52 [4.87-6.04]	5.15 [4.47-5.82]	5.97* [5.10-6.85]	6.16** [5.45-6.86]	6.62** [5.83-7.41]
Stimulation to use AI based applications in learning processes (DSTIMUSE)	6.55*** [6.28-6.82]	7.30*** [6.99-7.60]	7.02*** [6.75-7.29]	7.27*** [6.67-7.88]	6.38*** [5.60-7.16]	6.65*** [5.85-7.46]	7.03*** [6.08-7.98]	7.40*** [6.66-8.13]	7.61*** [6.77-8.44]
Autonomous use of AI based applications in learning processes (DSELFUSE)	5.78*** [5.53-6.04]	6.47*** [6.18-6.76]	6.06*** [5.78-6.35]	6.05*** [5.45-6.65]	5.21 [4.54-5.87]	6.20** [5.47-6.93]	6.74*** [5.88-7.59]	7.10*** [6.43-7.77]	7.42*** [6.69-8.15]
Autonomous use of AI based applications in other contexts (OSELFUSE)	5.84*** [5.58-6.09]	6.08*** [5.75-6.41]	5.58*** [5.38-5.86]	6.29*** [5.63-6.95]	5.22 [4.48-5.96]	6.11** [5.44-6.77]	6.84*** [5.90-7.79]	6.59*** [5.81-7.37]	6.44*** [5.52-7.37]
Level of influence generated by AI based applications (AIINFL)	5.37** [5.12-5.63]	5.77*** [5.50-6.04]	5.20 [4.95-5.45]	5.81* [5.19-6.43]	5.21 [4.56-5.86]	5.67 [5.00-6.34]	5.66 [4.79-6.53]	5.48 [4.78-6.18]	6.25** [5.41-7.09]
Usefulness of AI based applications (AIU)	6.60*** [6.36-6.85]	7.48*** [7.22-7.73]	6.98*** [6.74-7.23]	7.67*** [7.13-8.20]	7.03*** [6.42-7.64]	6.87*** [6.30-7.44]	7.55*** [6.85-8.26]	7.71*** [7.13-8.28]	7.77*** [7.05-8.48]
Effectiveness of AI based applications (AIE)	6.41*** [6.16-6.66]	7.02*** [6.76-7.26]	6.81*** [6.57-7.04]	7.13*** [6.56-7.70]	6.78*** [6.20-7.35	6.52*** [5.89-7.14]	6.87*** [6.06-7.67]	7.07*** [6.47-7.67]	7.42*** [6.69-8.15]
Easiness to use AI based applications	6.51*** [6.26-6.75]	7.46*** [7.21-7.72]	7.38*** [7.13-7.64]	7.39*** [6.81-7.98]	7.46*** [6.81-8.10]	6.65*** [5.95-7.36]	7.45*** [6.71-8.18]	7.90*** [7.35-8.44]	7.91*** [7.20-8.62]

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(AIEU)									
Trust in the outcomes of AI based applications (TRAI)	5.92*** [5.66-6.17]	6.32*** [6.05-6.60]	6.08*** [5.86-6.30]	6.74*** [6.18-7.31]	6.07** [5.40-6.74]	5.76* [5.09-6.43]	6.42*** [5.60-7.24]	6.37*** [5.81-6.93]	6.39*** [5.72-7.06]
Balanced Trust Teachers/AI (TRBAL) (*)	1.40*** [1.11-1.70]	1.67*** [1.37-1.98]	1.53*** [1.29-1.78]	1.08** [0.31-1.85]	1.97*** [1.20-2.73]	2.30*** [1.60-3.00]	1.82*** [0.90-2.73]	1.74*** [0.99-2.48]	1.62*** [0.84-2.39]
Personalization of the learning process (LPER)	5.80*** [5.57-6.03]	5.95*** [5.69-6.21]	5.48*** [5.23-5.73]	6.03*** [5.38-6.67]	5.31 [4.74-5.88]	5.73 [5.00-6.46]	5.39 [4.52-6.27]	6.36*** [5.74-6.98]	6.09** [5.30-6.89]
Level of concern about privacy (W1)	4.12*** [3.78-4.46]	4.86 [4.46-5.26]	5.01 [4.69-5.35]	5.44 [4.53-6.35]	5.08 [4.05-6.10]	4.37 [3.42-5.32]	4.67 [3.51-5.82]	5.02 [3.99-6.05]	5.62 [4.57-6.68]
Level of concern about loss of skills (W2)	4.16*** [3.83-4.50]	5.63*** [5.22-6.03]	5.38* [5.04-5.72]	5.62 [4.71-6.53]	4.96 [3.97-5.96]	4.18 [3.23-5.14]	5.31 [4.18-6.43]	5.51 [4.47-6.55]	5.82 [4.69-6.96]
Level of concern about stereotyped solutions (W3)	3.88*** [3.57-4.20]	4.99 [4.62-5.36]	4.45*** [4.14-4.76]	4.75 [3.91-5.59]	4.49 [3.54-5.44]	3.67** [2.74-4.61]	4.68 [3.66-5.69]	4.92 [3.96-5.88]	5.80 [4.82-6.78]
Level of concern about lack of transparency (W4)	3.74*** [3.42-4.07]	4.51* [4.14-4.89]	4.01*** [3.70-4.32]	3.95 [3.05-4.85]	3.96* [3.05-4.87]	3.87* [2.91-4.83]	4.12 [3.04-5.19]	4.07* [3.15-4.99]	4.72 [3.73-572]
Level of concern about gender/race bias (W5)	3.54*** [3.20-3.89]	3.32*** [2.90-3.73]	2.97*** [2.65-3.29]	3.34*** [2.42-4.26]	3.08*** [2.16-3.99]	3.36*** [2.44-4.28]	2.17*** [1.40-2.94]	3.34** [2.35-4.33]	2.40*** [1.43-2.37]
Level of concern about absence of conscience&ethics (W6)	3.84*** [3.48-4.19]	3.99*** [3.55-4.42]	3.39*** [3.05-3.73]	3.89* [2.91-4.86]	3.40** [2.42-4.37]	3.51** [2.56-4.46]	2.58*** [1.67-3.50]	3.16** [2.06-4.26]	2.83*** [1.84-3.82]
Level of concern about possible addiction (W7)	4.27*** [3.48-4.19]	4.45* [4.02-4.87]	4.28*** [3.92-4.63]	4.74 [3.77-5.70]	4.27 [3.27-5.27]	4.62 [3.56-5.68]	3.91 [2.66-5.17]	4.67 [3.56-5.77]	5.00 [3.83-6.17]

Level of concern about generation of false information (W8)	4.24*** [3.88-4.61]	4.99 [4.55-5.42]	4.69 [4.34-5.04]	4.90 [3.92-5.89]	4.62 [3.56-5.68]	4.38 [3.32-5.43]	4.44 [3.37-5.52]	4.66 [3.59-5.73]	5.35 [4.30-6.40]
Level of concern about unclear liability (W9)	3.96*** [3.61-4.31]	4.43** [4.02-4.84]	4.08*** [3.76-4.41]	4.03* [3.11-4.96]	4.20 [3.25-5.16]	3.61** [2.61-4.61]	3.31** [2.34-4.29]	4.65 [3.62-5.67]	5.24 [4.16-6.31]
Level of concern about non-compliance with copyright (W10)	3.96*** [3.60-4.31]	4.14*** [3.73-4.54]	3.76*** [3.42-4.09]	4.73 [3.75-5.71]	3.90* [2.90-4.91]	3.71* [2.73-4.69]	3.67* [2.65-4.68]	4.22 [3.17-5.27]	4.15 [3.08-5.23]
Level of concern about risk for democracy (W11)	3.85*** [3.50-4.21]	3.64*** [3.25-4.04]	3.40*** [3.07-3,72]	3.94* [2.96-4.91]	3.63 [2.68-4.57]	3.93* [2.91-4.96]	2.19*** [1.34-3.05]	3.47** [2.45-4.48]	3.18*** [2.20-4.16]
Level of concern about greater difficulty to find a job (W12)	4.27*** [3.92-4.62]	4.83 [4.40-5.25]	4.62 [4.26-4.99]	4.86 [3.87-5.84]	4.44 [3.45-5.43]	4.42 [3.41-5.43]	4.06 [2.88-5.23]	4.53 [3.45-5.62]	5.05 [3.92-6.18]
Level of concern about negative impact on environment (W13)	4.06*** [3.70-4.42]	4.01*** [3.60-4.43]	3.81*** [3.47-4.14]	3.83* [2.83-4.82]	3.80* [2.90-4.71]	3.77* [2.75-4.78]	3.83* [2.72-4.95]	4.06 [2.99-5.13]	4.03 [2.99-5.06]
Level of interest determined by customization (I1)	4.00*** [3.67-4.33]	5.37* [5.00-5.75]	5.05 [4.74-5.37]	5.90* [5.06-6.75]	4.64 [3.70-5.58]	4.47 [3.51-5.43]	5.36 [4.16-6.57]	4.89 [3.92-5.86]	5.69 [4.77-6.61]
Level of interest determined by complementarity with human capability (I2)	4.00*** [3.68-4.32]	4.99 [4.63-5.34]	5.06 [4.75-5.38]	5.30 [4.44-6.17]	3.98* [3.12-4.84]	4.32 [3.32-5.31]	4.73 [3.54-5.92]	4.53 [3.58-5.47]	5.38 [4.50-6.26]
Level of interest determined by	4.05*** [3.72-	5.20 [4.83-	5.04 [4.72	5.74 [4.90-6.58]	4.33 [3.50-	4.66 [3.74-	4.91 [3.68-6.14]	4.86 [3.96-	5.97* [5.02-

integrability with human capability (I3)	4.39]	5.57]	5.36]		5.16]	5.58]		5.76]	6.93]
Level of interest determined by reduction of human error (I4)	4.24*** [3.90-4.58]	5.34 [4.95-5.74]	5.23 [4.91 5.55]	6.08* [4.23-5.94]	4.63 [3.72-5.55]	4.36 [3.37-5.34]	5.26 [4.10-6.41]	4.77 [3.83-5.72]	5.89 [4.98-6.82]
Level of interest determined by preventing offences (I5)	4.10*** [3.75-4.45]	4.77 [4.39-5.15]	4.39*** [3.75-4.45]	4.97 [4.08-5.86]	3.94* [3.03-4.84]	4.34 [3.40-5.28]	4.53 [3.33-5.73]	4.61 [3.67-5.56]	5.13 [4.17-6.10]
Level of interest determined by optimized finding of links among elements & problem solutions (I6)	4.33*** [3.97-4.68]	5.65*** [5.27-6.03]	5.35* [5.04-5.67]	6.15** [5.30-6.99]	4.58 [3.59-5.57]	4.82 [3.77-5.87]	5.41 [4.27-6.55]	5.68 [4.72-6.66]	6.18* [5.29-7.07]
Level of interest determined by optimization of resources usage (I7)	4.50** [4.14-4.86]	5.60** [5.22-5.98]	5.41* [5.10-5.72]	6.20* [5.32-7.09]	4.62 [3.69-5.56]	4.95 [3.89-6.01]	5.49 [4.32-6.66]	5.20 [4.28-6.13]	6.62*** [5.76-7.47]
Level of interest determined by prevention of disinformation (I8)	4.30*** [3.94-4.67]	5.34 [4.80-5.57]	4.62* [4.30-4.93]	5.73 [4.84-6.61]	3.73** [2.86-4.59]	4.39 [3.39-5.38]	4.38 [3.20-5.56]	4.88 [3.90-5.87]	6.03* [5.18-6.88]
Level of interest determined by more job opportunities (I9)	4.38*** [4.03-4.74]	5.29 [4.89-5.70]	4.70 [4.36-5.03]	5.78 [4.91-6.65]	3.53** [2.57-4.47]	4.58 [3.56-5.60]	5.09 [3.97-6.20]	5.39 [4.43-6.34]	5.27 [4.27-6.28]

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Table 3. Mean values of the survey indicators (defined in the first column on the left) reported for the sets of Iraqi university students who participated in the survey grouped by their sex: Iraqi female students all majors (IRAQ F), Iraqi male students all majors (IRAQ F), Romanian bachelor female students in Computer Science (Bach R F), Romanian bachelor male students in Computer Science (Bach R M). For the sake of completeness, data concerning the total of the Iraqi students all majors (IRAQ tot) and the total of the Romanian bachelor students are also shown.

Indicator	**Mean IRAQ Tot**	**Mean IRAQ F**	**Mean IRAQ M**	**Mean Bach R Tot**	**Mean Bach R F**	**Mean Bach R M**
Individual Digital Skills (IDC)	6.74*** [6.44-6.83]	6.49*** [6.35-6.63]	7.01*** [6.88-7.13]	7.88*** [7.71-8.06]	7.80*** [7.51-8.10]	7.92*** [7.70-8.14]
Digital Skills: information management (IDC1)	4.66*** [4.52-4.80]	4.36*** [4.16-4.55]	4.97 [4.77-5.18]	7.74*** [7.47-8.02]	8.01*** [7.51-8.51]	7.62*** [7.9-8.95]
Digital Skills: interaction (IDC2)	5.50*** [5.03-5.47]	5.25* [5.03-5.47]	5.75*** [5.54-5.96]	7.89*** [7.61-8.16]	8.32*** [7.85-8.78]	7.69*** [7.35-8.02]
Digital Skills: digital content creation	4.32*** [4.17-4.47]	3.97*** [3.76-4.18]	4.68** [4.48-4.90]	7.09*** [6.80-7.38]	7.60*** [7.09-8.11]	6.84*** [6.49-7.20]

(IDC3)						
Digital Skills: devices and personal data protection (IDC4)	4.84* [4.68-4.99]	4.48*** [4.26-4.69]	5.20 [4.98-5.42]	6.91 [6.61-7.22]	7.05*** [6.53-7.57]	6.85*** [6.47-7.23]
Digital Skills: technical problem solving (IDC5)	4.39*** [4.24-4.54]	3.90*** [3.69-4.11]	4.90 [4.68-5.11]	7.26*** [6.97-7.54]	7.17*** [6.68-7.67]	7.30*** [6.95-7.64]
Level of information owned about AI (AIINF)	5.86*** [5.75-5.98]	5.61*** [5.45-5.77]	6.14*** [5.98-6.30]	7.52*** [7.33-7.71]	7.30*** [6.91-7.70]	7.62*** [7.41-7.84]
Ability to recognize AI based applications (AIREC)	5.87*** [5.76-5.99]	5.57*** [5.40-5.74]	6.20*** [6.03-6.36]	7.79*** [7.59-7.98]	7.46*** [7.11-7.81]	7.94*** [7.71-8.17]
Stimulation to use AI based applications in learning processes (DSTIMUSE)	6.99*** [6.86-7.12]	6.86*** [6.67-7.04]	7.14*** [6.96-7.33]	4.97 [4.64-5.30]	4.70 [4.21-5.18]	5.10 [4.66-5.53]
Autonomous use of AI based applications in learning processes (DSELFUSE)	6.17*** [6.04-6.30]	6.07*** [5.89-6.25]	6.29 *** [6.11-6.47]	7.07*** [6.80-7.34]	7.29*** [6.88-7.70]	6.96*** [6.62-7.31]
Autonomous use of AI based applications in other contexts (OSELFUSE)	5.93*** [5.80-6.07]	5.88*** [5.69-6.08]	6.00*** [5.82-6.77]	6.43*** [6.08-6.93]	6.29*** [5.74-6.85]	6.49*** [6.06-6.93]
Level of influence generated by AI based applications (AIINFL)	5.48*** [5.35-5.60]	5.32*** [5.14-5.50]	5.65*** [5.49-5.82]	5.58*** [5.27-5.89]	5.68** [5.17-6.19]	5.53* [5.14-5.92]
Usefulness of AI based applications (AIU)	7.10*** [6.99-7.22]	7.00*** [6.83-7.17]	7.23*** [7.07-7.39]	7.86*** [7.63-8.09]	7.91*** [7.51-8.32]	7.84*** [7.56-8.12]

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Effectiveness of AI based applications (AIE)	6.80*** [6.69-6.92]	6.64*** [6.48-6.81]	6.99*** [6.83-7.15]	6.96*** [6.72-7.20]	7.20*** [6.79-7.60]	6.85*** [6.55-7.15]
Easiness to use AI based applications (AIEU)	7.16*** [7.04-7.28]	7.04*** [6.87-7.22]	7.31*** [7.15-7.47]	8.09*** [7.86-8.32]	8.51*** [8.10-8.92]	7.89*** [7.61-8.17]
Trust in the outcomes of AI based applications (TRAI)	6.17*** [6.04-6.30]	6.13*** [5.96-6.30]	6.19*** [6.03-6.35]	5.86*** [5.61-6.11]	6.32*** [5.94-6.69]	5.64*** [5.32-5.95]
Balanced Trust Teachers/AI (TRBAL) (*)	1.64*** [1.51-1.77]	1.74*** [1.54-1.93]	1.55*** [1.36-1.73]	2.67*** [2.40-2.94]	3.01*** [2.57-3.45]	2.51*** [2.17-2.85]
Personalization of the learning process (LPER)	5.80*** [5.69-5.92]	5.78*** [5.62-5.95]	5.82*** [5.66-5.99]	6.62*** [6.34-6.90]	7.15*** [6.71-7.57]	6.37*** [6.02-6.72]
Level of concern about privacy (W1)	4.74** [4.57-4.90]	4.77 [4.54-5.01]	4.70* [4.45-4.94]	6.00*** [5.63-6.37]	6.50*** [5.88-7.12]	5.76** [5.30-6.22]
Level of concern about loss of skills (W2)	5.06 [4.89-5.23]	4.93 [4.69-5.17]	5.18 [4.94-5.42]	7.13*** [6.81-7.46]	7.52*** [7.01-8.04]	6.95*** [6.54-7.35]
Level of concern about stereotyped solutions (W3)	4.49*** [4.33-4.64]	4.35*** [4.16-4.57]	4.61*** [4.38-4.83]	6.36*** [6.03-6.70]	6.99*** [6.45-7.53]	6.06*** [5.64-6.49]
Level of concern about lack of transparency (W4)	4.08*** [4.93-4.24]	3.97*** [3.75-4.19]	4.17*** [3.95-4.40]	5.46** [5.13-5.79]	5.82** [5.27-6.36]	5.30 [4.88-5.71]
Level of concern about gender/race bias (W5)	3.28*** [3.11-3.44]	3.22*** [2.99-3.45]	3.30*** [3.07-3.54]	2.89*** [2.53-3.26]	3.41*** [2.79-4.04]	2.65*** [2.20-3.09]
Level of concern about absence of conscience&ethics	3.72*** [3.54-3.89]	3.75*** [3.50-4.00]	3.66*** [3.41-3.91]	4.49* [4.08-4.89]	5.12 [4.40-5.84]	4.19** [3.70-4.67]

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(W6)						
Level of concern about possible addiction (W7)	4.43*** [4.25-4.61]	4.63** [4.37-4.89]	4.20*** [3.96-4.45]	5.13 [4.72-5.54]	5.54 [4.84-6.24]	4.94 [4.43-5.45]
Level of concern about generation of false information (W8)	4.72** [4.54-4.90]	4.60** [4.34-4.85]	4.81 [4.56-5.06]	6.93*** [6.55-7.30]	7.49*** [6.91-8.06]	6.66*** [6.18-7.13]
Level of concern about unclear liability (W9)	4.22*** [4.05-4.39]	4.10*** [3.86-4.34]	4.29*** [4.06-4.53]	5.75*** [5.38-6.12]	6.22*** [5.63-6.81]	5.53* [5.06-6.00]
Level of concern about non-compliance with copyright (W10)	4.07*** [3.90-4.24]	4.10*** [3.86-4.34]	4.02*** [3.76-4.26]	5.32 [4.91-5.72]	5.98** [5.31-6.64]	5.01 [4.50-5.51]
Level of concern about risk for democracy (W11)	3.70*** [3.53-3.86]	3.70*** [3.46-3.94]	3.67*** [3.43-3.91]	4.28*** [3.86-4.69]	4.54 [3.86-5.21]	4.15** [3.63-4.67]
Level of concern about greater difficulty to find a job (W12)	4.63*** [4.45-4.81]	4.57*** [4.32-4.82]	4.68*** [4.42-4.93]	6.38*** [5.99-6.77]	7.13*** [6.51-7.75]	6.02*** [5.53-6.51]
Level of concern about negative impact on environment (W13)	4.06*** [3.90-4.24]	4.29*** [4.05-4.54]	3.82*** [3.58-4.06]	4.59* [4.17-5.01]	5.82* [5.10-6.53]	4.01*** [3.50-4.51]
Level of interest determined by customization (I1)	4.91 [4.75-5.07]	4.80 [4.57-5.03]	5.02 [4.79-5.25]	6.84*** [6.52-7.16]	7.63*** [7.18-8.09]	6.47*** [6.06-6.87]
Level of interest determined by complementarity with	4.74** [4.59-4.90]	4.56*** [4.34-4.79]	4.92 [4.69-5.14]	6.58*** [6.25-6.91]	7.10*** [6.61-7.58]	6.34*** [5.91-6.77]

human capability (I2)						
Level of interest determined by integrability with human capability (I3)	4.83** [4.67-4.99]	4.64** [4.42-4.86]	5.03 [4.80-5.25]	6.86*** [6.55-7.17]	7.32*** [6.81-7.82]	6.64*** [6.24-7.03]
Level of interest determined by reduction of human error (I4)	5.00 [4.84-5.17]	4.77 [4.54-5.00]	5.23* [5.00-5.47]	6.64*** [6.31-6.98]	7.00*** [6.48-7.52]	6.47*** [6.04-6.90]
Level of interest determined by preventing offences (I5)	4.56*** [4.40-4.73]	4.48*** [4.24-4.71]	4.66* [4.43-4.89]	5.64*** [5.29-5.97]	6.48*** [5.91-7.04]	5.24 [4.81-5.67]
Level of interest determined by optimized finding of links among elements & problem solutions (I6)	5.20* [5.04-5.36]	5.04 [4.80-5.27]	5.37* [5.13-5.60]	7.03*** [6.71-7.35]	7.68*** [7.18-8.19]	6.72*** [6.32-7.12]
Level of interest determined by optimization of resources usage (I7)	5.24** [5.08-5.40]	5.00 [4.77-5.24]	5.48*** [5.25-5.72]	7.19*** [6.86-7.51]	7.90*** [7.39-8.42]	6.84*** [6.43-7.25]
Level of interest determined by prevention of disinformation (I8)	4.73** [4.57-4.90]	4.53*** [4.30-4.77]	4.93 [4.70-5.16]	5.50** [5.14-5.87]	6.71*** [6.10-7.32]	4.93 [4.50-5.36]
Level of interest determined by more job opportunities (I9)	4.88 [4.71-5.05]	4.84 [4.60-5.09]	4.95 [4.71-5.19]	6.04** [5.66-6.42]	6.94*** [6.34-7.54]	5.60* [5.13-6.08]